US011675975B2

(12) **United States Patent**
Mote et al.

(10) **Patent No.: US 11,675,975 B2**
(45) **Date of Patent: Jun. 13, 2023**

(54) WORD CLASSIFICATION BASED ON PHONETIC FEATURES

(71) Applicant: **Google LLC**, Mountain View, CA (US)

(72) Inventors: **Nicolaus T. Mote**, Palo Alto, CA (US); **Ryan P. Doherty**, San Jose, CA (US)

(73) Assignee: **Google LLC**, Mountain View, CA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 233 days.

(21) Appl. No.: **16/915,298**

(22) Filed: **Jun. 29, 2020**

(65) **Prior Publication Data**

US 2020/0327281 A1 Oct. 15, 2020

Related U.S. Application Data

(63) Continuation of application No. 14/478,033, filed on Sep. 5, 2014, now abandoned.

(60) Provisional application No. 62/042,671, filed on Aug. 27, 2014.

(51) **Int. Cl.**

G06F 40/237	(2020.01)
G06F 16/903	(2019.01)
G06F 40/30	(2020.01)
G06F 40/242	(2020.01)
G06F 40/279	(2020.01)

(52) **U.S. Cl.**

CPC ***G06F 40/237*** (2020.01); ***G06F 16/90344*** (2019.01); ***G06F 40/242*** (2020.01); ***G06F 40/279*** (2020.01); ***G06F 40/30*** (2020.01)

(58) **Field of Classification Search**

None

See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

5,812,863	A *	9/1998	Ishikawa	G06F 40/253 715/257
6,018,736	A *	1/2000	Gilai	G06F 16/3329 707/999.005
6,108,627	A *	8/2000	Sabourin	G10L 15/187 704/E15.02
6,134,528	A *	10/2000	Miller	G06F 40/284 704/E13.011
6,236,965	B1 *	5/2001	Kim	G10L 15/187 704/E15.02
6,385,579	B1 *	5/2002	Padmanabhan	G10L 15/063 704/243
6,393,399	B1 *	5/2002	Even	G10L 15/193 704/235

(Continued)

OTHER PUBLICATIONS

Cook, Paul, and Suzanne Stevenson. "Automatically identifying the source words of lexical blends in English," Computational Linguistics 36.1 (2010): 129-149.

(Continued)

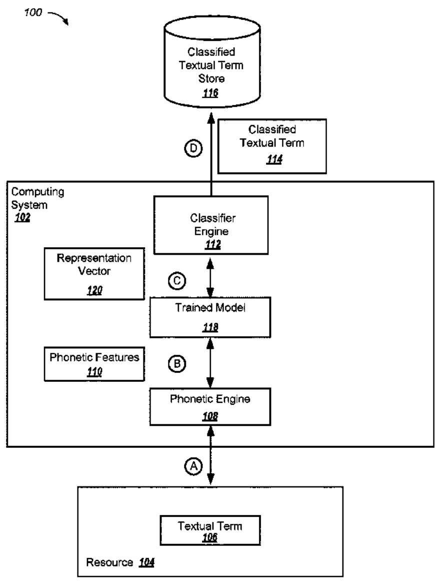
Primary Examiner — Jonathan C Kim

(74) *Attorney, Agent, or Firm* — Fish & Richardson P.C.

(57) **ABSTRACT**

Methods, systems, and apparatus, including computer programs encoded on a computer storage medium, for obtaining a textual term; determining, by one or more computers, a vector representing a phonetic feature of the textual term; comparing the vector representing the phonetic feature of the textual term with a reference vector representing a phonetic feature of a reference textual term; and classifying the textual term based on the comparing the vector with the reference vector.

13 Claims, 4 Drawing Sheets



]

(56) References Cited

U.S. PATENT DOCUMENTS

6,411,932	B1 *	6/2002	Molnar	G10L 13/00	704/254
6,976,019	B2 *	12/2005	Davallou	G06F 16/30	704/238
7,165,032	B2	1/2007	Bellegarda		
7,283,964	B1	10/2007	Geilhufe		
7,353,164	B1 *	4/2008	Bellegarda	G06F 40/232	704/10
9,164,983	B2 *	10/2015	Liu	G06F 40/126	
2002/0052740	A1 *	5/2002	Charlesworth	G06F 16/685	704/E15.02
2002/0065794	A1 *	5/2002	Fruensgaard	G06F 16/3338	
2002/0087313	A1 *	7/2002	Lee	G06Q 30/06	704/E15.044
2002/0152246	A1 *	10/2002	Critchlow	G06F 40/53	715/265
2003/0187649	A1 *	10/2003	Logan	G10L 15/26	704/E15.045
2004/0054533	A1 *	3/2004	Bellegarda	G10L 15/187	704/254
2005/0060156	A1 *	3/2005	Corrigan	G10L 13/04	704/270.1
2006/0241944	A1 *	10/2006	Potter	G06F 40/247	704/254
2006/0282266	A1 *	12/2006	Lopez-Barquilla	G10L 15/18	704/E15.018
2008/0046405	A1 *	2/2008	Olds	G06F 16/3322	
2008/0077396	A1 *	3/2008	Hsu	G06F 40/274	704/10
2008/0091413	A1 *	4/2008	El-Shishiny	G06F 16/322	704/10
2008/0104056	A1	5/2008	Li et al.		
2008/0147381	A1 *	6/2008	Yu	G06F 40/268	704/255
2008/0183696	A1 *	7/2008	Lagunas	G06F 40/232	707/999.005
2008/0189605	A1 *	8/2008	Kay	G06F 40/274	715/257
2009/0240488	A1 *	9/2009	White	G10L 15/30	345/173
2009/0254819	A1 *	10/2009	Song	G06F 40/242	715/257
2010/0179801	A1 *	7/2010	Huynh	G06F 40/56	704/1
2010/0180198	A1 *	7/2010	Iakobashvili	G06F 40/232	715/257
2011/0010178	A1 *	1/2011	Lee	G06F 40/129	704/E13.011
2011/0093259	A1 *	4/2011	Saffer	G10L 15/06	704/E11.001
2011/0184723	A1 *	7/2011	Huang	G06F 40/205	704/8
2011/0295897	A1 *	12/2011	Gao	G06F 16/3322	707/780
2012/0173574	A1 *	7/2012	Homma	G10L 15/19	707/E17.101
2013/0080174	A1 *	3/2013	Nishiyama	G10L 15/22	704/260
2013/0124474	A1 *	5/2013	Anderson	G06F 16/3338	707/634
2013/0173258	A1 *	7/2013	Liu	G06F 40/40	704/9
2013/0282645	A1 *	10/2013	Culbertson	G10L 15/18	706/52
2013/0283156	A1 *	10/2013	Al Badrashiny	G06F 40/232	715/257
2014/0372119	A1 *	12/2014	Parada	G06F 16/957	707/706
2015/0006441	A1 *	1/2015	Suzuki	G06F 16/9535	706/11
2016/0062979	A1 *	3/2016	Mote	G06F 16/90344	704/9

OTHER PUBLICATIONS

International Search Report and Written Opinion in International Application No. PCT/US2015/045352, dated Dec. 3, 2015, 15 pages.

Mikolov, Tomas et al., "Distributed Representations of Words and Phrases and their Compositionality", Proceedings of NIPS, 2013, 9 pages.

Mikolov, Tomas et al., "Efficient Estimation of Word Representations in Vector Space", Proceedings of Workshop at ICLR, 2013, 12 pages.

Mikolov, Tomas et al., "Linguistic Regularities in Continuous Space Word Representations", Proceedings of NAACL HLT, 2013, 6 pages.

Paaß et al., "SVM Classification Using Sequences of Phonemes and Syllables," Aug. 23, 2002, pp. 373-384.

Sriram et al., "Phonetic Distance Based Cross-lingual Search," International Conference on Natural Language Processing, Dec. 22, 2004, pp. 1-5.

* cited by examiner

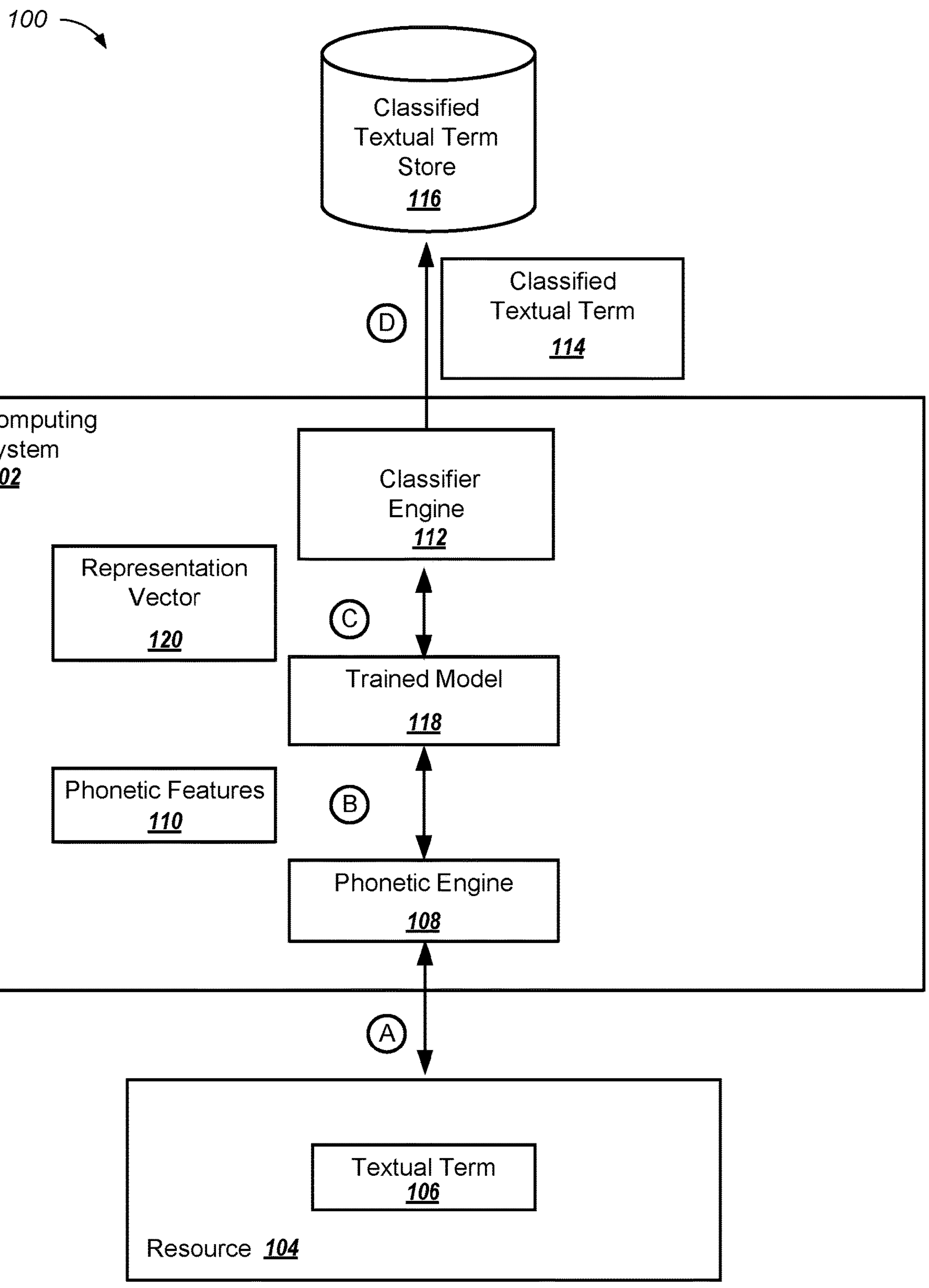

100
Classified Textual Term Store 116
D
Classified Textual Term 114
Computing System 102
Classifier Engine 112
Representation Vector 120
C
Trained Model 118
Phonetic Features 110
B
Phonetic Engine 108
A
Textual Term 106
Resource 104

FIG. 1

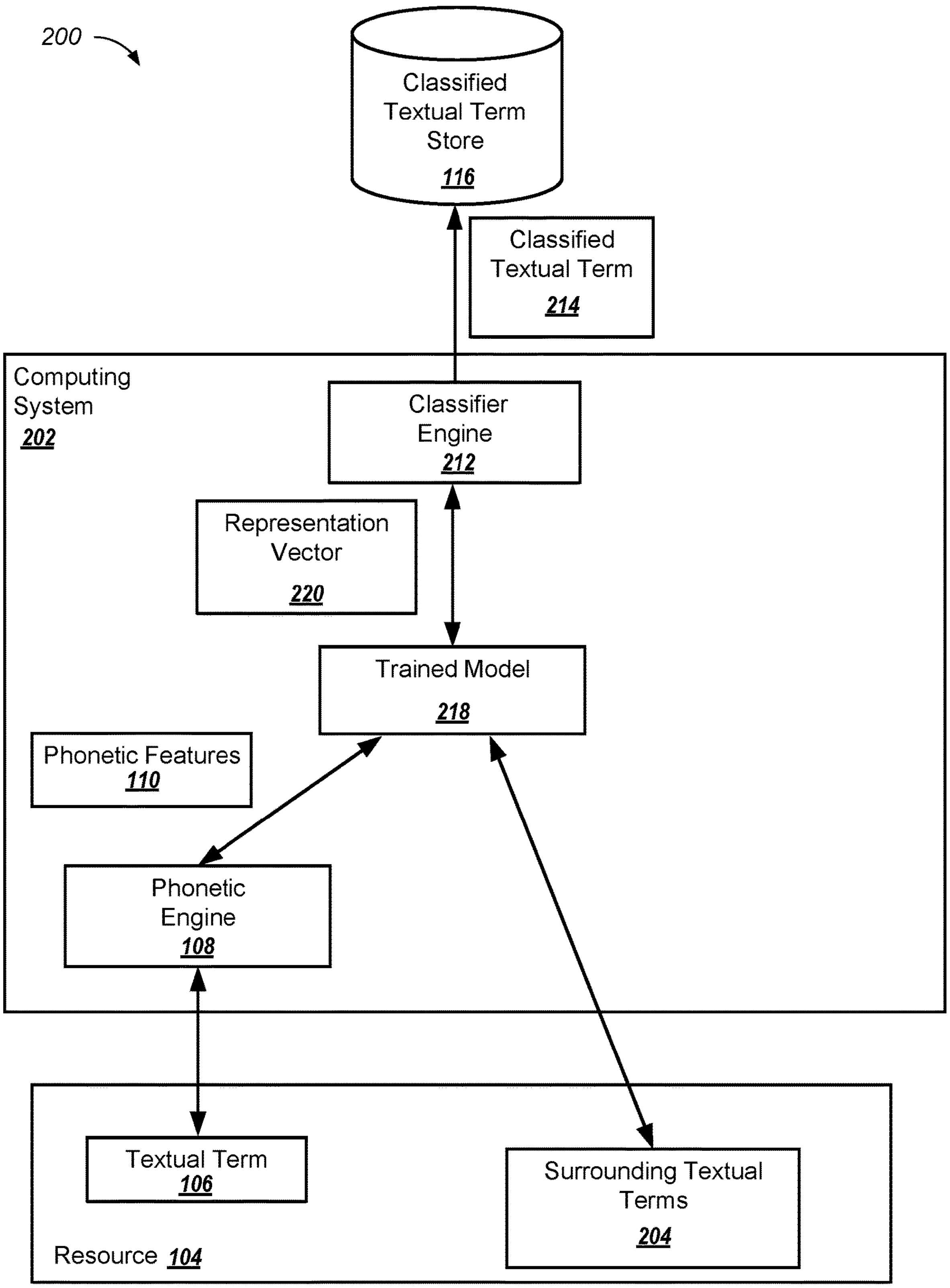

200
Classified Textual Term Store 116
Classified Textual Term 214
Computing System 202
Classifier Engine 212
Representation Vector 220
Trained Model 218
Phonetic Features 110
Phonetic Engine 108
Textual Term 106
Surrounding Textual Terms 204
Resource 104

FIG. 2

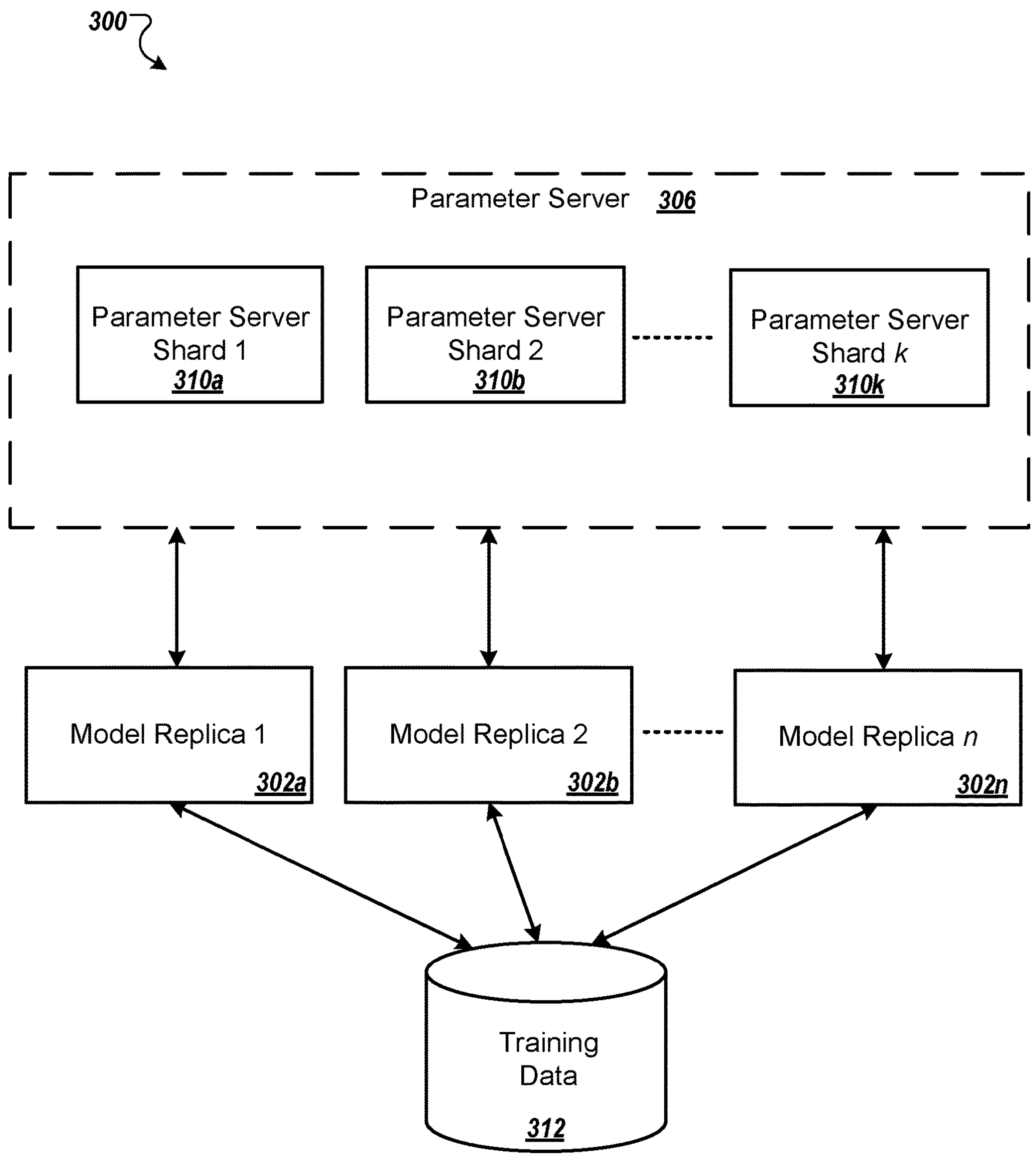

300
Parameter Server 306
Parameter Server Shard 1 310a
Parameter Server Shard 2 310b
Parameter Server Shard k 310k
Model Replica 1 302a
Model Replica 2 302b
Model Replica n 302n
Training Data 312

FIG. 3

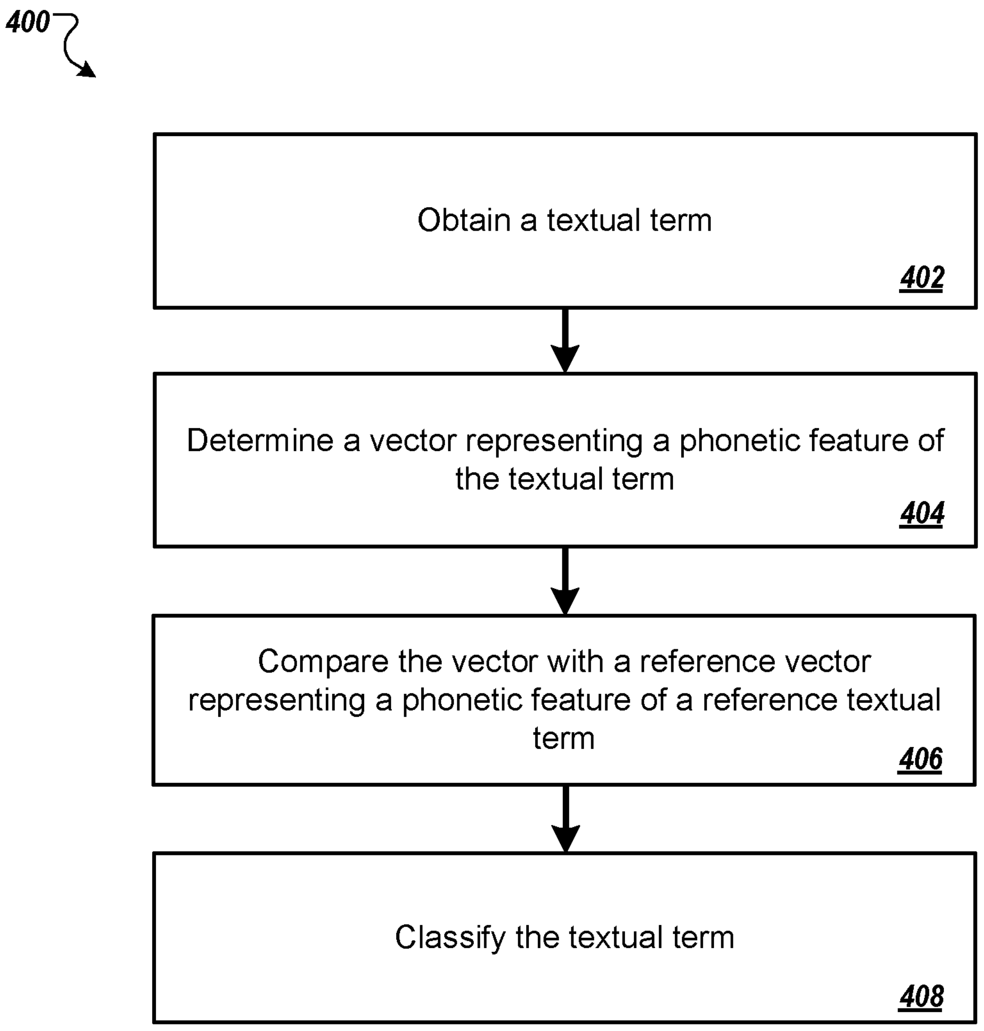

400
Obtain a textual term
402
Determine a vector representing a phonetic feature of the textual term
404
Compare the vector with a reference vector representing a phonetic feature of a reference textual term
406
Classify the textual term
408

FIG. 4

WORD CLASSIFICATION BASED ON PHONETIC FEATURES

CROSS-REFERENCE TO RELATED APPLICATION

This application is a continuation application of, and claims priority to, U.S. patent application Ser. No. 14/478,033, titled "WORD CLASSIFICATION BASED ON PHONETIC FEATURES," filed on Sep. 5, 2014, which application claims the benefit under 35 U.S.C. § 119(e) of U.S. Provisional Application Ser. No. 62/042,671, filed on Aug. 27, 2014. The disclosure of each of the foregoing applications is incorporated herein by reference.

BACKGROUND

This specification relates to using features of a textual term to classify the textual term.

SUMMARY

According to one innovative aspect of the subject matter described in this specification, phonetic features of textual terms such as pronunciation of the textual terms may be generated. A model for processing textual terms may be trained using the phonetic features. The model may be used to generate a representation of the phonetic features. The representation of the phonetic features of a textual term may be used to classify the textual term. The representation of the phonetic features of a textual term may be compared with a representation of phonetic features of another textual term to determine a relationship between the two textual terms. The phonetic features may be used augment a word-based model to provide a more comprehensive representation for textual terms.

In general, one innovative aspect of the subject matter described in this specification can be embodied in methods that include the actions of obtaining a textual term; determining, by one or more computers, a vector representing a phonetic feature of the textual term; comparing the vector representing the phonetic feature of the textual term with a reference vector representing a phonetic feature of a reference textual term; and classifying the textual term based on the comparing the vector with the reference vector.

These and other implementations can each optionally include one or more of the following features. Obtaining the textual term may include obtaining the textual term from a resource stored at a remote computer. Obtaining the textual term may include obtaining the textual term from a search query. Determining the vector representing the phonetic feature of the textual term may include determining a pronunciation of the textual term.

The textual term may include a plurality of characters. Determining the vector representing the phonetic feature of the textual term may include determining a first vector representing a phonetic feature of a subset of the plurality of characters of the textual term. Classifying the textual term may include determining that the subset of the plurality of characters of the textual term is similar to the reference textual term based on the comparing the vector with the reference vector; and in response to determining that the subset of the plurality of characters of the textual term is similar to the reference textual term, associating a definition of the reference textual term to the subset of the plurality of characters of the textual term.

The actions may include determining a second vector representing a phonetic feature of a second subset of the plurality of characters of the textual term; comparing the second vector with a second reference vector representing a phonetic feature of a second reference textual term; determining that the second subset of the plurality of characters is similar to the second reference textual term based on comparing the second vector with the second reference vector; and in response to determining that the second subset of the plurality of characters is similar to the second reference textual term, associating a definition of the second reference textual term to the second subset of the plurality of characters of the textual term.

Comparing the vector with the reference vector may include determining a cosine distance between the vector and the reference vector.

Classifying the textual term may include determining that the cosine distance is within a specific distance; and in response to determining that the cosine distance is within the specific distance, classifying the textual term as being similar to the reference textual term.

Classifying the textual term may include determining a likelihood that the textual term is similar to the reference textual term; and classifying the textual term based on the likelihood at the textual term is similar to the reference textual term.

Classifying the textual term may include determining that the textual term is similar to the reference textual term; and in response to determining that the textual term is similar to the reference textual term, associating a definition of the reference textual term to the textual term.

Obtaining the textual term may include obtaining one or more textual terms that are surrounding the textual term. Determining the vector representing the phonetic feature of the textual term may include determining the vector using (i) the phonetic feature of the textual term and (ii) the one or more textual terms that are surrounding the textual term.

Advantageous implementations may include one or more of the following features. A system can use phonetic features to classify certain types of textual terms that may not be classified using textual features, such as cognate words, invented words, lemmatization of words, word misspelling, hashtags, or alternative spelling of words. A system can use phonetic features to derive semantic relationships between words that are similar in sounds and concept but not in usage. A system can use phonetic features to augment a word-based model to provide a more comprehensive representation for any objects of interests including textual terms.

The details of one or more implementations are set forth in the accompanying drawings and the description below. Other potential features and advantages will become apparent from the description, the drawings, and the claims.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a block diagram of an example system.

FIG. **2** is a block diagram of an example system that uses phonetic features of a textual term to augment a word-based model.

FIG. **3** is a block diagram of an example system for training a model.

FIG. **4** is a flow chart illustrating an example process for classifying a textual term using phonetic features.

Like reference numbers and designations in the various drawings indicate like elements.

DETAILED DESCRIPTION

FIG. **1** is a block diagram of an example system **100**. The system **100** can be used to classify a textual term using the phonetic features of the textual term. A textual term is a sequence of one or more letters. For example, a textual term may include a word having a dictionary definition, a word without a dictionary definition, a compounded word, a concatenation of textual characters, textual metadata embedded in a resource, or any textual representation of a textual or non-textual resource. The system **100** compares a vector representing the phonetic features (e.g., the pronunciation of the textual term) of the textual term with one or more vectors representing phonetic features of one or more other textual terms to classify the textual term. Examples of classifying a textual term include determining a definition of the textual term, determining other textual terms that are related to the textual term, determining a relationship between the textual term and another textual term, or determining a relationship between the textual term and a non-textual object,

The system **100** includes a resource **104**, a computing system **102**, and a classified textual term store **116**. In general, the resource **104** may be any resource that is associated with a textual term **106**. The computing system **120** may be a remote server system that receives the textual term **106** as input, and based on phonetic features of the textual term **106**, provides a classification of the textual term **106** as output. The functions performed by the computing system **120** can be performed by individual computer systems or can be distributed across multiple computer systems.

The computing system **120** includes a phonetic engine **108**, a trained model **118**, and a classifier engine **112**. The phonetic engine **108** derives one or more phonetic features **110** of the textual term **106**. The trained model **118** generates a representation vector **120** that represents the phonetic features of the textual term **106** in a vector space. The classifier engine **112** classifies the textual term **106** based on the representation vector **120**. For example, the classifier engine **112** may compare the representation vector **120** with other representation vectors generated by the trained model **118** in the vector space, and the classifier engine **112** may classify the textual term **106** based on the comparison. The classifier engine **112** outputs a classified textual term **114** that represents a classification of the textual term **106**. The classified textual term **114** is stored in the classified textual term store **116**.

The resource **104**, the computing system **102**, and the classified textual term store **116** may be communicatively coupled using a wired network or wireless network or a combination of both. The network can include, for example, a wireless cellular network, a wireless local area network (WLAN) or Wi-Fi network, a Third Generation (3G) or Fourth Generation (4G) mobile telecommunications network, a wired Ethernet network, a private network such as an intranet, a public network such as the Internet, or any appropriate combination of networks.

FIG. **1** also illustrates an example flow of data, shown in stages (A) to (C). Stages (A) to (D) may occur in the illustrated sequence, or they may occur in a suitable sequence that is different than in the illustrated sequence.

During stage (A), the computing system **120** obtains the textual term **106** in the resource **104**. In some implementations, the resource **104** may be a textual resource that includes the textual term **106**. For example, the resource **104** may be a document in a corpus of documents, where the textual term **106** is included as a word in the document. As another example, the resource **104** may be the source code for a webpage, where the textual term **106** is included in the source code. In some implementations, the resource **104** may be a non-textual resource that is represented by the textual term **106**. For example, the resource **104** may be an image, and the textual term **106** may be a caption of the image. As another example, the resource **104** may be a data object, where the textual term **106** is metadata associated with the data object. In some implementations, the resource **104** may be dynamically generated. For example, the resource **104** may be a search query, where the textual term **106** is a search term in the search query. As another example, the resource **104** may be a trending search term, as determined by another computing system.

During stage (B), the phonetic engine **108** determines the phonetic features of the textual term **106**, and generates phonetic features **110**. In some implementations, the phonetic features **110** include a predicted pronunciation of the textual term. The pronunciation of the textual term can be predicted using a number of suitable techniques. For example, the phonetic engine **108** may use a pronunciation dictionary to predict the pronunciation of the textual term **106**. As another example, the phonetic engine **108** may use a set of acoustic rules to predict the pronunciation of the textual term **106**. As another example, the phonetic engine **108** may input the textual term **106** to a trained acoustic model to generate a predicted pronunciation of the textual term **106**. In some implementations, the phonetic features **110** include an acoustic signal representing the predicted pronunciation of the textual term. For example, the phonetic engine **108** may input the textual term **106** to a trained text-to-speech model to generate the acoustic signal representing the predicted pronunciation of the textual term **106**.

In some implementations, the phonetic engine **108** separates the textual term **106** into multiple textual terms, and determines the phonetic features of each respective textual term. For example, for an invented textual term "CompuVehicle," the phonetic engine **108** may separate the textual term into two textual terms "Compu" and "Vehicle," and determines the pronunciations of each of "Compu" and "Vehicle." In some implementations, the phonetic features **110** include the phonetic features of the textual term **106** and the phonetic features of the separated textual terms. For example, the phonetic features **110** of the textual term "CompuVehicle" may include the pronunciations of "CompuVehicle," "Compu," "Vehicle," "CompuVe," "hicle," and so on.

During stage (C), the trained model **118** determines a representation vector **120** based on the phonetic features **110**. The representation vector **120** may be mapped to a vector space that includes reference vectors representing phonetic features of known textual terms. In some implementations, the trained model **118** is trained using these known textual terms, and the reference vectors are generated by the trained model **118**.

In some implementations, the trained model **118** includes an embedding function that receives the phonetic features **110** and, in accordance with a set of embedding function parameters, applies a transformation to the phonetic features **110** that maps the phonetic features **110** into a continuous high-dimensional numeric representation. For example, the embedding function can apply a transformation to the phonetic features **110** to map the phonetic features **110** into a floating point representation vector **120**. In some implementations, the trained model **118** includes a neural network model that receives the phonetic features **110** and processes the phonetic features **110** through multiple hidden layers to generate the representation vector **120**.

In cases where the phonetic features **110** include the phonetic features of the textual term **106** and the phonetic features of the separated textual terms, the trained model **118** may determine a respective representation vector for each of the textual terms. For example, for the textual term "CompuVehicle" described above, the trained model **118** may determine a respective representation vector for each of the textual terms "CompuVehicle," "Compu," "Vehicle," "CompuVe," "hicle," and so on.

During stage (D), the classifier engine **112** classifies the textual term **106** using the representation vector **120**, and stores the classified textual term **114** in the classified textual term store **116**. The classifier **110** can be any multiclass or multilabel classifier, e.g., a multiclass logistic regression classifier, a multiclass support vector machine classifier, or a Bayesian classifier.

The classifier engine **112** may compare the representation vector **120** with one or more reference vectors in the vector space. In some implementations, the classifier engine **112** determines a distance, e.g., a cosine distance, between the representation vector **120** and one or more reference vectors in the vector space, and classifies the textual term **106** based on the cosine distance. If the cosine distance between the representation vector **120** and a particular reference vector is within a specific vector distance, the classifier engine **112** may classify that the textual term **106** is related to the textual term associated with the particular reference vector.

For example, the classifier engine **112** may determine that the cosine distance between the representation vector of "CompuVehicle" is not within the specific vector distance with any reference vectors in the vector space. However, the classifier engine **112** may determine that the cosine distance between the representation vector of the separated textual term "Compu" is within the specific vector distance with the reference vector of a known textual term "Computer," and the classifier engine **112** may classify that the separated textual term "Compu" is related to the known textual term "Computer." As another example, the classifier engine **112** may determine that the representation vector of the separated textual term "Vehicle" is numerically equal to the reference vector of a known textual term "Vehicle," and the classifier engine **112** may classify that the separated textual term "Vehicle" is equivalent of the known textual term "Vehicle."

As another example, a resource **104** may include a textual term **106** "Vehecle" that is an unintended spelling error of a known textual term "Vehicle." The classifier engine **112** may determine that the representation vector of the textual term **106** "Vehecle" is within the specific vector distance to the reference vector of the known textual term "Vehicle," and the classifier engine **112** may classify that the textual term **106** "Vehecle" is related to the known textual term "Vehicle" because their phonetic features (e.g., pronunciations) are similar. Consequently, even textual terms with spelling errors can still be useful for subsequent analysis.

In some implementations, the classified textual term **114** is a data structure indicating the classification of the textual term **106**. For example, the classified textual term **114** for the textual term "CompuVehicle" may be an ordered list {"CompuVehicle", "Computer", "Vehicle"}, indicating that the classifier engine **112** has determined that the known textual terms "Computer" and "Vehicle" are related to the textual term "CompuVehicle."

In some implementations, the classified textual term **114** is represented by a word score vector, where each field of the word score vector corresponds to a respective known textual term in a set of known textual terms. For example, each field of the word score vector may include a score indicating a probability that the definition of the textual term **106** corresponds to the definition of the respective known textual term. The classifier engine **112** may determine that the textual term **106** is similar to a particular known textual term if the particular known textual term has the highest score in the word score vector.

The classified textual term **114** stored in the classified textual term store may be used to provide a definition for the textual term **106**. The classified textual term **114** stored in the classified textual term store may be used to provide a relationship between the textual term **106** and other known textual terms. The classified textual term **114** stored in the classified textual term store may be used to provide a relationship between the textual term **106** and other known textual terms. The classified textual term **114** stored in the classified textual term store may be used to train an updated model for generating representation vectors. The classified textual term **114** stored in the classified textual term store may be used as input to another computing system.

FIG. **2** is a block diagram of the example system **200** that can use phonetic features of a textual term to augment a word-based model. In general, a word-based model uses textual terms that surround a particular textual term to classify the particular textual term. In some implementations, a word-based model discards textual terms that the computing system cannot classify, and valuable information may be lost as the results. For example, a textual term that has been invented by an author may not be captured by a word-based model because the surrounding textual terms may not provide sufficient information for the classification of the invented textual term. Phonetic features may be used to provide a complementary signal to a word-based model, resulting in a more comprehensive vector space for classifying textual terms. The example system **200** includes a resource **104**, a computing system **202**, and a classified textual term store **116**. The computing system **202** includes a phonetic engine **108**, a trained model **218**, and a classifier engine **212**.

The resource **104** includes the textual term **106** and surrounding textual terms **204**. For example, if the textual term **106** is at position t in a sequence of textual terms, the surrounding textual terms **204** are known words at position t−N, . . . , t−1, t+1, . . . , t+N, respectively, where N is a predetermined integer value.

The trained model **218** uses one or both of the phonetic features **110** or the surrounding textual terms **204** to determine a representation vector **220** of the textual term **106**. In some implementations, the trained model **218** includes a word-based embedding function that receives a sequence of textual terms and, in accordance with a set of embedding function parameters, applies a transformation to the textual terms that maps the textual terms into a continuous high-dimensional word-based vector space. For example, the word-based embedding function may be a combining embedding function. A combining embedding function maps each textual term in the sequence of textual terms to a respective continuous high-dimensional word-based vector space, for example, to a respective high-dimensional vector of floating point numbers, based on current parameter values of the embedding function, e.g., as stored in a lookup table, and then merges the respective floating point vectors into a single merged vector. The merged floating point representation vector can be used by the classifier engine **212** to classify the textual term **106**.

In some implementations, the trained model **218** uses the phonetic features **110** to modify the floating point representation vector to determine the representation vector **220**. For example, the trained model **218** may add one or more dimensions in the word-based vector space to represent the phonetic features of textual terms. The trained model **218** may map the phonetic features **110** to the additional dimensions, and the values in the additional dimensions may be used by the classifier engine **212** to classify the textual term **106**.

The classifier engine **212** uses the representation vector **220** to determine a classified textual term **214**. The classifier **212** receives the representation vector **220** generated by the trained model **218** and classifies the textual term **106** similar to the classifier **112**. In some implementations, if the classifier engine **212** determines that the values in the word-based vector space cannot be used to classify the textual term **106**, the classifier engine **212** uses the values in the additional dimensions corresponding to the phonetic features **110** to classify the textual term **106**. In some implementations, after the classifier engine **212** classifies the textual term **106** using values in the word-based vector space, the classifier engine **212** classifies the textual term **106** using values in the additional dimensions corresponding to the phonetic features **110**, and compares the two classifications. The classifier engine **212** may select one or both classifications to be included in the classified textual term **214**.

FIG. **3** is a block diagram of an example system **300** that can train a model. In general, a model such as the trained model **118** or the trained model **218** may be trained in any number of ways. The example system **300** illustrates parallel training of a model, where the trained model can be used in systems such as the example systems **100** and **200**.

The model receives input and generates an output based on the received input and on values of the parameters of the model. For example, a model may receive data identifying phonetic features of textual terms and, based on the phonetic features of the textual terms and on the parameters of the model, may generate a vector that represents a textual term. The model may be composed of a single level of linear or non-linear operations or may be composed of multiple levels of linear or non-linear operations. An example of a model is a neural network with one or more hidden layers.

The model can be trained using training data, i.e., the training data in training data database **312**. The training data in the training data database **312** are inputs for which the desired output, i.e., the output that should be generated by the model, is known. In order to train the model, i.e., find optimal values of the model parameters, an objective function is developed that is a measure of the performance of the model on the set of training data as a function of the model parameters. The optimal values of the parameters of the model can then be found by finding a minimum of the objective function. In particular, multiple iterations of a stochastic gradient descent procedure can then be performed to find the optimal values of the parameters.

The example system **300** includes multiple model replicas **302***a-n*. Each of the model replicas **302***a-n* is an identical instance of a model and can be implemented as one or more computer programs and data deployed to be executed on a computing unit. Advantageously, the computing units are configured so that they can operate independently of each other. In some implementations, only partial independence of operation is achieved, for example, because replica instances share some resources.

A computing unit may be, e.g., a computer, a core within a computer having multiple cores, or other hardware or software within a computer capable of independently performing the computation for the model replica. Each model replica **302***a-n* operates independently from each of the other model replicas **302***a-n* and is configured to communicate with the training data database **312** and a parameter

server **306** through a network, e.g., a local area network (LAN) or wide area network (WAN), e.g., the Internet, in order to compute delta values for the parameters of the model. A delta value for a parameter is a value that the replica has determined is to be applied to the current value of the parameter so that it approaches its optimal value.

The parameter server **306** maintains the current values of the parameters of the model and updates the values as the results of training are uploaded by the replicas. The functionality of the parameter server **306** may be partitioned among multiple parameter server shards **310***a-k*. That is, each of the parameter server shards **310***a-k* maintains values of a respective subset of the parameters of the model, such that the parameters of the model are partitioned among the parameter server shards **310***a-k*. Each parameter server shard **310***a-k* is implemented on a respective independent computing unit. Advantageously, the computing units are configured so that they can operate independently of each other. In some implementations, only partial independence of operation is achieved, for example, because replica instances share some resources.

Each of the parameter server shards **310***a-k* provides values of parameters to the model replicas **302***a-n*, receives delta values of the parameters from the model replicas **302***a-n*, and updates stored values of the parameters based on the received delta values independently from each other parameter server shard.

FIG. **4** is a flow diagram that illustrates an example process **400** for classifying a textual term using phonetic features. The process **400** may be performed by data processing apparatus, such as the example system **100** described above, the example system **200** described above, or another data processing apparatus.

The system obtains a textual term (**402**). For example, the computing system **120** may access a textual term **106** in a resource **104**. In some implementations, the system obtains the textual term from a resource stored at a remote computer. In some other implementations, the system obtains the textual term from a search query.

The system determines a vector representing a phonetic feature of the textual term (**404**). For example, the phonetic engine **108** may determine the phonetic features of the textual term **106**, and generates phonetic features **110**. The trained model **118** may determine a representation vector **120** based on the phonetic features **110**.

In some implementations, the system determines the vector representing the phonetic feature of the textual term by determining a pronunciation of the textual term. For example, the phonetic engine **108** may use a pronunciation dictionary to predict the pronunciation of the textual term **106**. As another example, the phonetic engine **108** may use a set of acoustic rules to predict the pronunciation of the textual term **106**. As another example, the phonetic engine **108** may input the textual term **106** to a trained acoustic model to generate a predicted pronunciation of the textual term **106**.

The system compares the vector representing the phonetic feature of the textual term with a reference vector representing a phonetic feature of a reference textual term (**406**). For example, the classifier engine **112** may compare the representation vector **120** with one or more reference vectors in the vector space.

The system classifies the textual term based on the comparing the vector with the reference vector (**408**). In some implementations, the system compares the vector with the reference vector by determining a cosine distance between the vector and the reference vector.

In some implementations, the system classifies the textual term by determining that the cosine distance is within a specific distance. In response to determining that the cosine distance is within the specific distance, the system classifies the textual term as being similar to the reference textual term. For example, a resource **104** may include a textual term **106** "Vehecle" that is an unintended spelling error of a known textual term "Vehicle." The classifier engine **112** may determine that the representation vector of the textual term **106** "Vehecle" is within the specific vector distance to the reference vector of the known textual term "Vehicle," and the classifier engine **112** may classify that the textual term **106** "Vehecle" is related to the known textual term "Vehicle" because their phonetic features (e.g., pronunciations) are similar.

In some implementations, the system classifies the textual term by determining a likelihood that the textual term is similar to the reference textual term. The system classifies the textual term based on the likelihood at the textual term is similar to the reference textual term. For example, the classified textual term **114** may be a word score vector, where each field of the word score vector corresponds to a respective known textual term in a set of known textual terms. Each field of the word score vector may include a score indicating a probability that the definition of the textual term **106** corresponds to the definition of the respective known textual term. The classifier engine **112** may determine that the textual term **106** is similar to a particular known textual term if the particular known textual term has the highest score in the word score vector.

In some implementations, the system classifies the textual term by determining that the textual term is similar to the reference textual term. In response to determining that the textual term is similar to the reference textual term, associating a definition of the reference textual term to the textual term.

The textual term can include multiple characters. The system determines the vector representing the phonetic feature of the textual term by determining a first vector representing a phonetic feature of a subset of the characters of the textual term. For example, for the textual term "CompuVehicle", the trained model **118** may determine a respective representation vector for a textual term "Compu." The system classifies the textual term by determining that the subset of the characters of the textual term is similar to the reference textual term based on the comparing the vector with the reference vector. In response to determining that the subset of the characters of the textual term is similar to the reference textual term, the system associates a definition of the reference textual term to the subset of the characters of the textual term. For example, the classifier engine **112** may determine that the cosine distance between the representation vector of the separated textual term "Compu" is within the specific vector distance with the reference vector of a known textual term "Computer," and the classifier engine **112** may classify that the separated textual term "Compu" is related to the known textual term "Computer."

The system determines a second vector representing a phonetic feature of a second subset of the characters of the textual term. For example, for the textual term "CompuVehicle", the trained model **118** may determine a respective representation vector for a textual term "Vehicle." The system compares the second vector with a second reference vector representing a phonetic feature of a second reference textual term. The system determines that the second subset of the characters is similar to the second reference textual term based on comparing the second vector with the second reference vector. In response to determining that the second subset of the characters is similar to the second reference textual term, the system associates a definition of the second reference textual term to the second subset of the characters of the textual term. For example, the classifier engine **112** may determine that the representation vector of the separated textual term "Vehicle" is numerically equal to the reference vector of a known textual term "Vehicle," and the classifier engine **112** may classify that the separated textual term "Vehicle" is equivalent of the known textual term "Vehicle."

In some implementations, the system obtains one or more textual terms that are surrounding the textual term. For example, the trained model **218** obtains surrounding textual terms **204**. The surrounding textual terms **204** may be all terms within a specific number of terms adjacent to the textual term **106**. The surrounding textual terms **204** may be all terms within a specific number of terms adjacent to the textual term **106**, excluding specific terms (e.g., "a", "an", "the", etc.). The system determines the vector representing the phonetic feature of the textual term by determining the vector using (i) the phonetic feature of the textual term and (ii) the one or more textual terms that are surrounding the textual term. For example, the trained model **218** may add one or more dimensions in the word-based vector space to represent the phonetic features of textual terms. The trained model **218** may map the phonetic features **110** to the additional dimensions, and the values in the additional dimensions may be used by the classifier engine **212** to classify the textual term **106**.

A number of implementations have been described. Nevertheless, it will be understood that various modifications may be made without departing from the spirit and scope of the disclosure. For example, various forms of the flows shown above may be used, with steps re-ordered, added, or removed.

Embodiments and all of the functional operations described in this specification may be implemented in digital electronic circuitry, or in computer software, firmware, or hardware, including the structures disclosed in this specification and their structural equivalents, or in combinations of one or more of them. Embodiments may be implemented as one or more computer program products, i.e., one or more modules of computer program instructions encoded on a computer-readable medium for execution by, or to control the operation of, data processing apparatus. The computer readable-medium may be a machine-readable storage device, a machine-readable storage substrate, a memory device, a composition of matter affecting a machine-readable propagated signal, or a combination of one or more of them. The computer-readable medium may be a non-transitory computer-readable medium. The term "data processing apparatus" encompasses all apparatus, devices, and machines for processing data, including by way of example a programmable processor, a computer, or multiple processors or computers. The apparatus may include, in addition to hardware, code that creates an execution environment for the computer program in question, e.g., code that constitutes processor firmware, a protocol stack, a database management system, an operating system, or a combination of one or more of them. A propagated signal is an artificially generated signal, e.g., a machine-generated electrical, optical, or electromagnetic signal that is generated to encode information for transmission to suitable receiver apparatus.

A computer program (also known as a program, software, software application, script, or code) may be written in any form of programming language, including compiled or interpreted languages, and it may be deployed in any form, including as a standalone program or as a module, component, subroutine, or other unit suitable for use in a computing environment. A computer program does not necessarily correspond to a file in a file system. A program may be stored in a portion of a file that holds other programs or data (e.g., one or more scripts stored in a markup language document), in a single file dedicated to the program in question, or in multiple coordinated files (e.g., files that store one or more modules, sub programs, or portions of code). A computer program may be deployed to be executed on one computer or on multiple computers that are located at one site or distributed across multiple sites and interconnected by a communication network.

The processes and logic flows described in this specification may be performed by one or more programmable processors executing one or more computer programs to perform functions by operating on input data and generating output. The processes and logic flows may also be performed by, and apparatus may also be implemented as, special purpose logic circuitry, e.g., an FPGA (field programmable gate array) or an ASIC (application specific integrated circuit).

Processors suitable for the execution of a computer program include, by way of example, both general and special purpose microprocessors, and any one or more processors of any kind of digital computer. Generally, a processor will receive instructions and data from a read only memory or a random access memory or both. The essential elements of a computer are a processor for performing instructions and one or more memory devices for storing instructions and data. Generally, a computer will also include, or be operatively coupled to receive data from or transfer data to, or both, one or more mass storage devices for storing data, e.g., magnetic, magneto optical disks, or optical disks. However, a computer need not have such devices. Moreover, a computer may be embedded in another device, e.g., a tablet computer, a mobile telephone, a personal digital assistant (PDA), a mobile audio player, a Global Positioning System (GPS) receiver, to name just a few. Computer readable media suitable for storing computer program instructions and data include all forms of non-volatile memory, media and memory devices, including by way of example semiconductor memory devices, e.g., EPROM, EEPROM, and flash memory devices; magnetic disks, e.g., internal hard disks or removable disks; magneto optical disks; and CD-ROM and DVD-ROM disks. The processor and the memory may be supplemented by, or incorporated in, special purpose logic circuitry.

To provide for interaction with a user, embodiments may be implemented on a computer having a display device, e.g., a CRT (cathode ray tube) or LCD (liquid crystal display) monitor, for displaying information to the user and a keyboard and a pointing device, e.g., a mouse or a trackball, by which the user may provide input to the computer. Other kinds of devices may be used to provide for interaction with a user as well; for example, feedback provided to the user may be any form of sensory feedback, e.g., visual feedback, auditory feedback, or tactile feedback; and input from the user may be received in any form, including acoustic, speech, or tactile input.

Embodiments may be implemented in a computing system that includes a back end component, e.g., as a data server, or that includes a middleware component, e.g., an application server, or that includes a front end component, e.g., a client computer having a graphical user interface or a Web browser through which a user may interact with an

implementation of the techniques disclosed, or any combination of one or more such back end, middleware, or front end components. The components of the system may be interconnected by any form or medium of digital data communication, e.g., a communication network. Examples of communication networks include a local area network ("LAN") and a wide area network ("WAN"), e.g., the Internet.

The computing system may include clients and servers. A client and server are generally remote from each other and typically interact through a communication network. The relationship of client and server arises by virtue of computer programs running on the respective computers and having a client-server relationship to each other.

An "engine" (or "software engine") refers to a software implemented input/output system that provides an output that is different from the input. An engine can be an encoded block of functionality, such as a library, a platform, a Software Development Kit ("SDK"), or an object.

While this specification contains many specifics, these should not be construed as limitations, but rather as descriptions of features specific to particular embodiments. Certain features that are described in this specification in the context of separate embodiments may also be implemented in combination in a single embodiment. Conversely, various features that are described in the context of a single embodiment may also be implemented in multiple embodiments separately or in any suitable subcombination. Moreover, although features may be described above as acting in certain combinations and even initially claimed as such, one or more features from a claimed combination may in some cases be excised from the combination, and the claimed combination may be directed to a subcombination or variation of a subcombination.

Similarly, while operations are depicted in the drawings in a particular order, this should not be understood as requiring that such operations be performed in the particular order shown or in sequential order, or that all illustrated operations be performed, to achieve desirable results. In certain circumstances, multitasking and parallel processing may be advantageous. Moreover, the separation of various system components in the embodiments described above should not be understood as requiring such separation in all embodiments, and it should be understood that the described program components and systems may generally be integrated together in a single software product or packaged into multiple software products.

Thus, particular embodiments have been described. Other embodiments are within the scope of the following claims. For example, the actions recited in the claims may be performed in a different order and still achieve desirable results.

What is claimed is:

1. A computer-implemented method, comprising:

obtaining an unknown textual term and other terms surrounding the unknown textual term with N word positions of the unknown textual term, wherein the unknown textual term is a textual term that has an unknown dictionary definition, and N is a predetermined integer value;

determining, by one or more computers, an unknown term vector representing (i) one or more phonetic features of the unknown textual term and (ii) the other terms surrounding the unknown textual term, including determining the unknown term vector using (i) the one or more phonetic features of the unknown textual term and (ii) the one or more other textual terms that are surrounding the unknown textual term;

classifying the unknown textual term based on (i) a word-based model that uses the representation of the one or more other textual terms that are surrounding the unknown textual term to classify the unknown textual term; and (ii) a classifier that compares the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space, wherein each reference vector represents a reference textual term having a known definition;

wherein classifying the unknown textual term comprises:

determining a level of similarity between the unknown textual term vector and each of the plurality of reference vectors; and

generating a classified textual term that includes a word score vector comprised of a plurality of fields that each correspond to a respective reference textual term having a known dictionary definition, wherein generating the classified textual term further includes determining a score for each respective field of the word score vector that is (i) based on the similarity determination of the unknown textual vector and the reference vector that represents the respective reference textual term that is associated with the respective field, and (ii) indicative of the probability that the definition of the unknown textual term corresponds to the definition of the respective reference textual term that is associated with the respective field; and

providing the classified textual term as an input to a word model, wherein the word model is configured to process the classified textual term and generate one or more representation vectors, based on the classified textual term.

2. The method of claim **1**, wherein classifying the unknown textual term based on (i) a word-based model that representation of the one or more other textual terms that are surrounding the unknown textual term; and (ii) a classifier that compares the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space comprises:

using the classifier to compare the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space only in response to determining that the word-based model cannot classify the unknown textual term.

3. The method of claim **1**, wherein classifying the unknown textual term based on (i) a word-based model that representation of the one or more other textual terms that are surrounding the unknown textual term; and (ii) a classifier that compares the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space further comprises:

using the classifier to compare the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space only in response to determining that the word-based model cannot classify the unknown textual term.

4. The method of claim **1**, wherein obtaining the unknown textual term comprises obtaining the unknown textual term from a resource stored at a remote computer.

5. The method of claim **1**, wherein obtaining the unknown textual term comprises obtaining the unknown textual term from a search query.

6. The method of claim **1**, wherein determining the unknown term vector representing the phonetic feature of the unknown textual term comprises determining a pronunciation of the unknown textual term.

7. A non-transitory computer-readable medium storing software having stored thereon instructions, which, when executed by one or more computers, cause the one or more computers to perform operations of:

obtaining an unknown textual term and other terms surrounding the unknown textual term with N word positions of the unknown textual term, wherein the unknown textual term is a textual term that has an unknown dictionary definition, and N is a predetermined integer value;

determining, by one or more computers, an unknown term vector representing (i) one or more phonetic features of the unknown textual term and (ii) the other terms surrounding the unknown textual term, including determining the unknown term vector using (i) the one or more phonetic features of the unknown textual term and (ii) the one or more other textual terms that are surrounding the unknown textual term;

classifying the unknown textual term based on (i) a word-based model that uses the representation of the one or more other textual terms that are surrounding the unknown textual term to classify the unknown textual term; and (ii) a classifier that compares the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space, wherein each reference vector represents a reference textual term having a known definition;

wherein classifying the unknown textual term comprises:

determining a level of similarity between the unknown textual term vector and each of the plurality of reference vectors; and

generating a classified textual term that includes a word score vector comprised of a plurality of fields that each correspond to a respective reference textual term having a known dictionary definition, wherein generating the classified textual term further includes determining a score for each respective field of the word score vector that is (i) based on the similarity determination of the unknown textual vector and the reference vector that represents the respective reference textual term that is associated with the respective field, and (ii) indicative of the probability that the definition of the unknown textual term corresponds to the definition of the respective reference textual term that is associated with the respective field; and

providing the classified textual term as an input to a word model, wherein the word model is configured to process the classified textual term and generate one or more representation vectors, based on the classified textual term.

8. The non-transitory computer-readable medium of claim **7**, wherein classifying the unknown textual term based on (i) a word-based model that representation of the one or more other textual terms that are surrounding the unknown textual term; and (ii) a classifier that compares the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space comprises:

using the classifier to compare the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space only in response to determining that the word-based model cannot classify the unknown textual term.

9. The non-transitory computer-readable medium claim **7**, wherein classifying the unknown textual term based on (i) a word-based model that representation of the one or more other textual terms that are surrounding the unknown textual term; and (ii) a classifier that compares the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space further comprises:

using the classifier to compare the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space only in response to determining that the word-based model cannot classify the unknown textual term.

10. The non-transitory computer-readable medium of claim **7**, wherein obtaining the unknown textual term comprises obtaining the unknown textual term from a resource stored at a remote computer.

11. The non-transitory computer-readable medium of claim **7**, wherein obtaining the unknown textual term comprises obtaining the unknown textual term from a search query.

12. The non-transitory computer-readable medium of claim **7**, wherein determining the unknown term vector representing the phonetic feature of the unknown textual term comprises determining a pronunciation of the unknown textual term.

13. A system comprising:

one or more processors and one or more computer storage media storing instructions that are operable, when executed by the one or more processors, to cause the one or more processors to perform operations comprising:

computers to perform operations of:

obtaining an unknown textual term and other terms surrounding the unknown textual term with N word positions of the unknown textual term, wherein the unknown textual term is a textual term that has an unknown dictionary definition, and N is a predetermined integer value;

determining, by one or more computers, an unknown term vector representing (i) one or more phonetic features of the unknown textual term and (ii) the other terms surrounding the unknown textual term, including determining the unknown term vector using (i) the one or more phonetic features of the unknown textual term and (ii) the one or more other textual terms that are surrounding the unknown textual term; and

classifying the unknown textual term based on (i) a word-based model that uses the representation of the one or more other textual terms that are surrounding the unknown textual term to classify the unknown textual term; and (ii) a classifier that compares the representation of the one or more phonetic features of the unknown textual term to each of a plurality of reference vectors in a vector space, wherein each reference vector represents a reference textual term having a known definition;

wherein classifying the unknown textual term comprises:

determining a level of similarity between the unknown textual term vector and each of the plurality of reference vectors; and

generating a classified textual term that includes a word score vector comprised of a plurality of fields that each correspond to a respective reference textual term having a known dictionary definition, wherein generating the classified textual term further includes determining a score for each respective field of the word score vector that is (i) based on the similarity determination of the unknown textual vector and the reference vector that represents the respective reference textual term that is associated with the respective field, and (ii) indicative of the probability that the definition of the unknown textual term corresponds to the definition of the respective reference textual term that is associated with the respective field; and

providing the classified textual term as an input to a word model, wherein the word model is configured to process the classified textual term and generate one or more representation vectors, based on the classified textual term.

* * * * *